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MANAGING THE FLOATING-OBJECT FISHERY FOR TROPICAL TUNAS IN THE EPO: ADDITIONAL PRECAUTIONARY MEASURES RECOMMENDED BY THE STAFF

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SUMMARY

The IATTC staff's 2020 risk analysis (SAC-11-08) for the tropical tuna fishery in the EPO indicates that the recent management measures (C-17-02), which expired at the end of 2020 and were extended for 2021 (C-20-06), are adequate in the short term. Nonetheless, the staff is recommending additional precautionary measures to ensure that these *status quo* conditions—defined as the average fishing mortality (*F*) during the most recent 3-year period (2017-2019) of the bigeye and yellowfin assessments — are not exceeded, for three reasons:

1. For bigeye tuna (BET), the risk analysis estimates a 50% probability that current fishing mortality (F_{cur}) is higher than the target reference point of maximum sustainable yield (MSY). However, the results of the risk analysis are bimodal (SAC-11-08), with a more pessimistic and a more optimistic group of models. The combined models in the pessimistic group indicate a 10% (or slightly higher) probability that the limit reference point has been exceeded;
2. Stock status indicators (SAC-12-05), in particular those for the floating-object (OBJ) fishery (number of sets, catch-per-set, and average weight for all three species), show long-term trends that could lead to increased *F* in the near future, thus jeopardizing the desired effect of the current measures for the purse-seine fishery (frozen capacity, 72-day closure, the *corralito* closure, daily active fish-aggregating device (FAD) limits).
3. Given the lack of stock assessment or an evaluated harvest strategy for skipjack, fishing mortality should not be increased beyond current levels.

There are several types of management measures that could be considered (*e.g.* measures summarized in SAC-12 INF-B). The staff reviewed the advantages and disadvantages of each option, as well as potential

solutions to mitigate or compensate the disadvantages (*e.g.* SAC-11 INF-M). The staff also weighed the management benefits against data and infrastructure shortcomings (*i.e.* for monitoring compliance) and concluded that an extended temporal closure, based on the previous year's number of OBJ sets (only if the *status quo* is exceeded), combined with individual-vessel daily active FAD limits, would be the best option for maintaining the *status quo* and thus prevent an increase in *F* within the management cycle. The closure would be for both OBJ and unassociated (NOA) set types, and apply to all purse-seine vessels, except those that historically made mostly NOA sets (vessels that have made 75% or more of their sets on unassociated schools in each of 3 of the past 5 years (2015-2019)). In addition to the measures already established in C-17-02 and extended through C-20-06, these two additional precautionary measures would help control the two remaining aspects of the fishery that are not sufficiently constrained (OBJ sets and FADs at sea), which, if left unconstrained, might allow fishing mortality to increase.

The staff is recommending the adoption of the additional measures in a multi-year (3-year, 2022-2024) conservation package for tropical tuna in the EPO (SAC-12-16). A multi-year package is desirable because it would provide stability in the conservation measures and allow time to: 1) improve the BET and YFT stock assessments, 2) develop a tagging-based assessment for SKJ (SAC-12-06), 3) improve the risk analysis framework before new management advice is needed, 4) develop assessments for other stocks (e.g. swordfish), and 5) focus on the ongoing Management Strategy Evaluation (MSE) process for tropical tunas.

1. BACKGROUND

New benchmark assessments are available for bigeye (BET) and yellowfin tuna (YFT) (SAC-11-06, SAC-11-07). These assessments represent a fundamental change from the staff's previous 'best assessment' approach: they are the basis for a 'risk analysis', in which a variety of reference models are used to represent plausible alternative hypotheses (SAC-11-08). In 2020, the staff concluded that the overall results of the bigeye risk analysis do not support changing the duration of the purse-seine closure, for two reasons. First, the probability that the target reference points (fishing mortality and spawning biomass corresponding to maximum sustainable yield; F_{MSY} and S_{MSY}) have been reached is at about 50%. Resolution C-16-02 does not specify an acceptable level of probability of exceeding these target reference points. However, the staff notes that 50% is a reasonable arbitrary reference level, considering that *S* will fluctuate around S_{MSY} as recruitment fluctuates, and *F* will likewise fluctuate around F_{MSY} due to interannual fluctuations in catchability and distribution of effort among purse-seine set types. Second, the overall results of the risk analysis for BET indicate that, although the probability that the limit reference points have been exceeded is not negligible for both *F* and *S*, they do not exceed the threshold level of 10% specified in Resolution C-16-02 for triggering an action (SAC-11-08).

However, the staff believes that the conservation and management measures that will replace Resolution C-17-02, which expired at the end of 2020 and were extended to 2021 (C-20-06), should include provisions to ensure that fishing mortality is not increased beyond the *status quo* (F_{cur})[1], for the following precautionary reasons. First, half of the models used in the risk analysis for BET are "pessimistic": combined, they indicate that the limit reference points for BET have already been exceeded by a probability of, or slightly over, 10% (SAC-11-08). Second, the stock status indicators (SAC-12-05), in particular those related to effort in the OBJ fishery, show long-term trends that, if they persist, would potentially lead to increased *F* in the near future, jeopardizing the desired effect of the current measures for the purse-seine fishery (frozen capacity, 72-day closure, the *corralito* closure, daily active FAD limits).

This is not the first time that the staff is recommending precautionary measures for tropical tunas additional to the provisions of C-17-02: measures to prevent further increases in fishing mortality have been

[1] Defined as the average fishing mortality (*F*) during the most recent three-year period (2017-2019) of the bigeye and yellowfin assessments.

proposed every year since 2018 (*e.g.* IATTC-94-03, FAD-04-01, IATTC-95-01). Such recommendations are aligned with the requirement in Article VII.1.h of the Antigua Convention to "adopt appropriate measures to prevent or eliminate over-fishing and excess fishing capacity and to ensure that levels of fishing effort do not exceed those commensurate with the sustainable use of the fish stocks covered by this Convention". Specifically, the staff recommended: (a) reductions of the active FAD limits, and (b) a limit on the combined total number of OBJ and NOA sets. This combination limit (OBJ+NOA), rather than just an OBJ set limit, was mainly for practical reasons: it is difficult to obtain accurate data on numbers of sets, by type, in a near real-time manner, which would be necessary to implement such a limit; set type determinations cannot be verified until the trip has been completed and the data processed[2]. Moreover, small YFT are also caught in NOA sets, and the 2019 YFT stock assessment indicated that its status was potentially a concern and could benefit from a limit on such sets. The SAC did not support this recommendation (SAC-10 report, Sec. 13), mainly due to concerns about a possible "race to fish", but also about the potential to exceed the desired OBJ set limits, given their operational advantages of OBJ sets over NOA sets in terms of locating fish, incidence of zero-catch sets, *etc*.

Recent research by the staff (FAD-05 INF-D) provides new guidance on the type of precautionary measures that should directly relate to fishing mortality. Specifically, that research has identified a direct relationship between the number of OBJ sets and fishing mortality for BET (for the ages targeted by these fisheries) estimated by the 2020 BET EPO stock assessment (SAC-11-06). This relationship was found to be significant, positive and linear, or near-linear, for three of the five OBJ fishery areas defined in the assessment, and for all OBJ fisheries combined. The relationship is particularly noteworthy in the equatorial offshore area, where the majority of the BET catch is occurring (*e.g*. around 75% of the OBJ BET catch in 2019 occurred in that area).

This new research indicates that an increase in the number of OBJ sets proportionally increases BET fishing mortality, and thus management measures that control the number of OBJ sets should limit fishing mortality for the species. In particular, to maintain the *status quo*, the additional management measures should be designed to keep the number of OBJ sets at the level that corresponds to the fishing mortality rates in the most recent assessments, so that the limit reference points are not breached. In this case, this fishing mortality rate is the average over the 2017-2019 period. Therefore, the management options should prevent the annual number of OBJ sets from exceeding the 2017-2019 average levels.

There are several types of management measures that could be considered to constrain the number of OBJ sets (*e.g*. measures summarized in SAC-12 INF-B). The staff reviewed the advantages and disadvantages of each option and weighted the management benefits against data and infrastructure shortcomings (*i.e*. for monitoring compliance) as well as against undesirable side effects (SAC-11 INF M). After these considerations, the staff concluded that an extended temporal closure for OBJ and NOA sets for all purse-seine vessels, except those that historically made mostly NOA sets, combined with individual-vessel daily active FAD limits, would be the best option for maintaining the *status quo* and thus preventing an increase in F within the management cycle.

These additional management measures are recommended by the staff based on the assumption that the Commission will adopt a 3-year management package, which was previously recommended by the staff (SAC-11-15) and the SAC (IATTC-95-02), for the 2022-2024 period at its next meeting in 2021 (SAC-12-16). A multi-year package is desirable because it provides stability to the conservation measures, allows time to improve the tropical tuna stock assessments (BET, YFT) and risk analysis before new management advice is needed, and allows time to develop stock assessments of other species (e.g. SKJ, swordfish). The

[2] Combining OBJ and NOA sets for reporting purposes might preserve data quality by eliminating the incentive to report OBJ sets as NOA sets, as might occur with a limit on OBJ sets only.

additional time would also allow staff and other stakeholders to focus on the ongoing management strategy evaluation (MSE) process, to formally evaluate alternative management strategies ability to achieve management objectives while facing multiple sources of uncertainty.

In the remainder of this document, the rationale behind the two additional recommended measures is presented in detail and the measures are fully described. An operational rule to define the duration of the extended temporal closure is also proposed, which is based on the previous year's number of OBJ sets. Considerations for compliance monitoring are also discussed. In the calculations conducted for this document, it is assumed that the capacity has not increased since 2017 due to it being frozen, and hence any changes in the capacity fishing are due to "random" changes arising from choices made by the fishing companies (*e.g.* fishing in the WCPO) or inoperable vessels.

2. EXTENDED TEMPORAL CLOSURE FOR FLOATING-OBJECT AND UNASSOCIATED SETS

2.1. Rationale for the measure

The staff recommends an extended temporal closure for both OBJ and NOA sets for all IATTC vessel size classes, except those that historically made mostly NOA sets (*i.e.* 75% or more of their sets on NOA in each of 3 of the past 5 years (2015-2019)) and are allowed to continue making NOA sets. This extended temporal closure will be appended to the end of the current 72-day closure. The length of this extended closure will be based on the number of OBJ sets made in the previous year, relative to the 2017-2019 average, to ensure the *status quo* is not exceeded.

The goal of the extended temporal closure is to control the number of OBJ sets, particularly to avoid increasing the fishing mortality on BET. However, the implementation of a management measure may impact other set types and species. Whereas the stock assessment for YFT shows that the stock is healthy and small to moderate increases in the fishing mortality are unlikely to change the status of the stock in the short term, there is no formal stock assessment for SKJ. Thus, the impact on SKJ of an extended temporal closure needs to be taken into consideration.

Management of SKJ has historically been tied to the status of BET (SKJ has approximately the same susceptibility as BET, but is more productive) because formal stock assessments for SKJ have not been possible. In particular, since the probability that fishing mortality for BET has exceeded its MSY level is 50%, an arbitrary level considered as reasonable by the staff, it could be considered that the *status quo* fishing mortality for SKJ is also appropriate. If an extended temporal closure for OBJ sets alone were to be put in place, effort transfer from OBJ sets to NOA sets may take place during the extended temporal closure. Assuming the extended temporal closure limits the number of OBJ sets to *status quo* levels and *F* is proportional to the number of OBJ sets, then the *F* for both BET and SKJ would remain the same for OBJ. However, the *F* on SKJ could increase due to the effort reallocation from OBJ to NOA sets during the extended temporal closure, if NOA sets were allowed.

To reduce the chance that effort reallocation from OBJ sets to NOA sets during the extended temporal closure leads to an increase in *F* on SKJ, the extended closure should apply to both OBJ and NOA sets. This extended closure will not limit effort reallocation for OBJ or NOA sets to dolphin-associated (DEL) sets. Some vessels that previously did not have a Dolphin Mortality Limit (DML) could apply for one, allowing them to switch from OBJ or NOA sets to DEL sets during the extended closure, but this may be unlikely if the duration of the closure is relatively short. Some vessels that already have DMLs, and typically conduct OBJ and NOA sets in addition to DEL sets, may switch to making more DEL sets during the extended closure. This is not perceived by the staff to be a concern because the yellowfin stock is healthy and the potential increase in *F* is unlikely to change the stock status within the recommended three-year management period.

An exemption should be made for vessels that historically mostly conducted NOA sets. These vessels are not contributing substantially to the increase in floating-object effort and do not have a large potential to increase fishing mortality on SKJ by switching from OBJ sets to NOA sets during the extended temporal closure. A cutoff of making 75% NOA sets in a year should be used to identify these vessels as this appears to be a clear threshold differentiating vessels with predominantly NOA fishing strategies (Figure 1).

An extended temporal closure that applies to both OBJ and NOA sets, which is triggered only in specific situations given an operational rule, has the following advantages:

a. A measure specifying days of closure has already been adopted by the Commission (*e.g.* Res. C-17-02, C-20-06).
b. Using the previous year's number of OBJ sets to trigger the operational rule:
    i. Does not generate the additional data demands and/or additional infrastructure needs for data processing that would be required for near real-time monitoring of the fishery.
    ii. Reduces problems associated with set type misreporting.
    iii. Allows for adjustments to be made to the reported set types, if necessary, using set type classification algorithms (see Appendices A and B).
c. Applying the extended closure to both OBJ and NOA sets reduces problems associated with set type misreporting during the closure period.
d. The DEL fishery will not be impacted, which is supported by the results of the current YFT assessment that indicates the stock is healthy.

2.2. Measure details

The operational rule that connects the increase in *F* (increase in number of OBJ sets) to the management action should be based on the Best Scientific Estimate (BSE) of the number of OBJ sets in the previous year (see Appendix A for a summary description of the methodology to derive the BSE; the statistical details of the BSE methodology are provided in Appendix B). This rule has the advantage that the BSE is based on analysis of relevant data from multiple sources collected during the year. This will help to mitigate the effect of any misreporting of set type on the estimated number of OBJ sets, particularly after the rule comes into force.

The operational rule will be applied as follows:

Days open in year i = Min[Days open in year i-1 x (average OBJ sets (2017- 2019) / OBJ sets in year i-1),

365 - 72]

The additional days representing the extended temporal closure of OBJ and NOA sets for year i is calculated as: [365 – (days open in year i) – 72].

The extra number of days of closure for a given number of OBJ sets based on the implementation of the operational rule is presented in Figure 2.

The details of the rule include:

1) The extended temporal closure will be calculated using OBJ sets for vessels of all size classes.
2) The extended closure will be for all vessels (covered under the current temporal closures) and for both OBJ and NOA sets.
3) The extended closure is appended to the end of the existing 72-day temporal closure for all set types.
4) Vessels that have made 75% or more of their sets on NOA in each of 3 of the past 5 years (2015-2019) will be allowed to make NOA sets during the extended closure, as long as they have an observer on board.
5) Only vessels with a DML and those satisfying (4) will be allowed at sea during the extended closure.

2.3. Compliance monitoring considerations

There are several considerations as regards compliance monitoring during the extended temporal closure. First, the set type classifications algorithm that will be applied as part of the BSE methodology (see Appendices A and B) can be used to evaluate whether reported set types during the closure period were accurate. Any cases of apparent misreporting of set types during the extended closure could be passed to the Compliance Committee for review. Second, it is noted that for compliance monitoring during the extended closure, a formal definition for an OBJ set may be required. This definition would not be adopted in the BSE methodology, however, since the set type algorithm is based on historical data, and thus the scientific definition should not be changed. Therefore, the Compliance Committee may wish to take into consideration both the scientific findings on misreporting and other indicators of misreporting based on a legal set type definition, as the interim definitions considered by the FAD WG (FAD-03b).

3. ADJUST THE LIMITS ON DAILY ACTIVE FADS

3.1. Rationale for the measure

The staff recommends individual-vessel limits (IVL) on the daily number of active FADs[3], computed independently for each vessel from its active FAD data for 2018-2019 (data prior to 2018 have not been provided to the IATTC staff).

Resolution C-17-02, now C-20-06, requires CPCs or their vessels to report, on a monthly basis, daily information on all active FADs to the Secretariat[4] and established capacity-class limits to control fishing mortality in the OBJ fishery (vessels with higher number of active FADs may make more OBJ sets or have increased efficiency, Lopez *et al*. (2014), FAD-04-01). However, vessels in the same capacity-class can have different strategies in the use of FADs and any fleetwide or capacity-class restrictions will impact some vessels more than others (FAD-04-01). Because the motivation is not to exceed 2018-2019 active FAD levels, the staff believes that, unlike with adjustments to capacity-class limits in C-17-02 and C-20-06, individual-vessel daily active FAD limits would prevent, or more efficiently limit, vessels increasing their use of active FADs with respect to the *status quo*.

The staff considers that establishing annual individual vessel limits on the number of daily active FADs is also essential to maintaining the *status quo* of other components of the fishery that are currently unregulated, such as total number of FADs at sea and deployments. Vessel-specific active FAD limits will indirectly prevent the total number of active FADs from increasing because each vessel will be limited to its level of FAD use over the 2018-2019 period. Moreover, by limiting active FADs per vessel, the number of deployments would be indirectly limited to some extent, provided remote activation does not occur or is not widespread (*i.e.* Resolution C-17-02 and C-20-06 prohibit remote activations). It is noted that within the current class categories specified in C-17-02/C-20-06, there are very different FAD fishing strategies (*e.g.* see section 3.1 in FAD-05-INF-A or FAD-05 INF-C), and adjusting the current capacity-class limits, *e.g.*, decreasing those limits to the average (or any other similar metric), would have a significant adverse effect on a number of vessels unnecessarily because the goal of the measure is to not exceed the *status quo*. Conversely, new capacity-class limits would still be significantly high or generous for an important segment of the fleet. As a consequence, some vessels would have to reduce their number of active FADs substantially while others would be allowed to increase their number of active FADs (e.g. SAC-11 INF-M, FAD-05 INF-A, FAD-05 INF-C), potentially exceeding total number of FADs at sea and deployments with regards *status quo*. As an example, even with active FAD restrictions in place, certain fleets significantly

[3] Resolution C-17-02 and C-20-06 define a FAD as 'active' when it is deployed at sea and the attached satellite buoy starts transmitting its location. FADs must be activated exclusively aboard a purse-seine vessel.

[4] FADs are currently identified using satellite buoys, per Resolution C-19-01

increased in recent years their use of active FADs in other oceans (Imzilen et al. 2020).

A fleetwide limit on active FADs is not proposed by the staff because the existing active FAD measures and reported data are by vessel and currently some vessels do not report, or report incompletely. To define a fleetwide limit, it would be necessary to extrapolate to those vessels that did not report during the past two years, which would be problematic without an accurate relationship between vessels' operational characteristics and the number of active FADs. This relationship cannot be obtained by grouping vessels according to their capacity-class categories, as is done in C-17-02 and C-20-06, because, as illustrated elsewhere (*e.g.* section 3.1 in FAD-05-INF-A and FAD-05 INF-C), FAD fishing strategies differ even within the capacity categories.

An annual IVL on the number of daily active FADs has the following advantages:

a. Since 2018, a limit on active FADs has been in force (Resolution C-17-02; C-20-06), and a system for collecting and reporting these data monthly already exists for all purse-seine vessels[5].
b. If individual-vessel limits on daily active FADs are established, vessels could not increase the use of active FADs with respect to the *status quo*, unlike with adjustments to capacity-class limits in C-17-02/C-20-06.
c. In general, vessels with higher numbers of active FADs make more OBJ sets (FAD-04-INF-A, SAC-11-INF-M), suggesting a potential relationship between active FADs and OBJ sets, and ultimately *F* (FAD-05 INF-D).

3.2. Measure details

Regarding the computation of the daily limit for each vessel, there are a number of options, among which, for instance, establishing that the IVL would be equal to the average of the maximum monthly number of active FADs (to account for seasonality) that the vessel reported during 2018-2019. In addition, all data from months corresponding to the vessel's observed closure period would be excluded, since active FAD data reported during closure periods may not represent accurate fishing/operational strategies for many vessels (*e.g*. SAC-11 INF-M, FAD-05 INF-A, FAD-05 INF-C). For vessels that have reported fewer than 12 individual months with active FAD data during 2018-2019, it would be necessary also to adopt a computational method: an option would be to request that they submit any missing data by, for example, 31 July 2021 (or any other date decided by the Commission), when their respective daily limits would be computed. If no data is reported by the agreed date for the missing period, it would be assumed that the vessel's active FAD use is zero for that particular time, and existing values would be used to compute the final IVLs. Finally, there is another category of vessels that should be addressed appropriately, those which have never reported active FAD data during 2018-2019, because they were not fishing on FADs during that period, because they were not fishing in the EPO, or because they simply did not report any data. Under the computational method described above, their adjusted limit would be zero, which might be consistent with the idea of a *status quo* but could be perceived as discriminatory for the vessels and for the flag Member concerned. For some of these vessels, this computation might be possible provided that active FAD data for 2018-2019 were to be reported. For other vessels, those that have never fished on FADs and would wish to do it, including as a complementary fishing strategy, it may be concluded that the best way forward would be to develop an equitable solution, still to be analyzed and defined by the Commission, compatible with the general thrust of these recommendations.

[5] During 2018-2019, 156 vessels reported active FAD data, partially or continuously. About 75% of the vessels reported during at least 12 months and 50% reported during at least 20 months

3.3. Compliance monitoring considerations

There are several considerations as regards compliance monitoring of the IVLs. First, independent verification of the reported data and other provisions included in the Resolutions (*i.e.* remote activation of FADs, C-17-02 and C-20-06), is not available. As noted previously (*e.g*. IATTC-94-02, SAC-10-19, FAD-03 INF-B, SAC-11-15), access to the high-resolution buoy data (ideally the same daily raw buoy data received by original users; *i.e*. vessels, fishing companies) and VMS data would help the staff to conduct independent verification of the mentioned issues. Second, not all vessels that appear to be using FADs are currently reporting active FAD data or have provided data for only part of the 2018-2019 period.

Improving data reporting, as mandated under C-17-02 and C-20-06, would make available active FAD data for all vessels that are required to report and allow for more accurate estimates of active FADs per vessel and globally. Thus, it would be desirable for the Commission to explore alternative mechanisms and provisions that improve data submission and quality, including, but not limited to, revising the guidelines developed by the FAD WG on buoy data reporting to match the recommendations of the staff, the SAC and the FAD WG itself (*e.g.* new reporting systems, such as direct access to raw satellite buoy data provided by buoy manufacturers to the original users; IATTC-94-02, FAD-03 INF-B, SAC-10-19, SAC-11-15), reinforcement or clarification of IATTC confidentiality policies, and capacity building workshops with stakeholders, as needed. In fact, improving data collection and data quality are actions that have been shown to be of unquestionable scientific value in the management of tuna stocks (*e.g.* SCRS/2019/075), and might provide the information necessary to allow a better understanding of the relationship between operational characteristics, active FADs, total FADs at sea, catches and, ultimately, number of sets.

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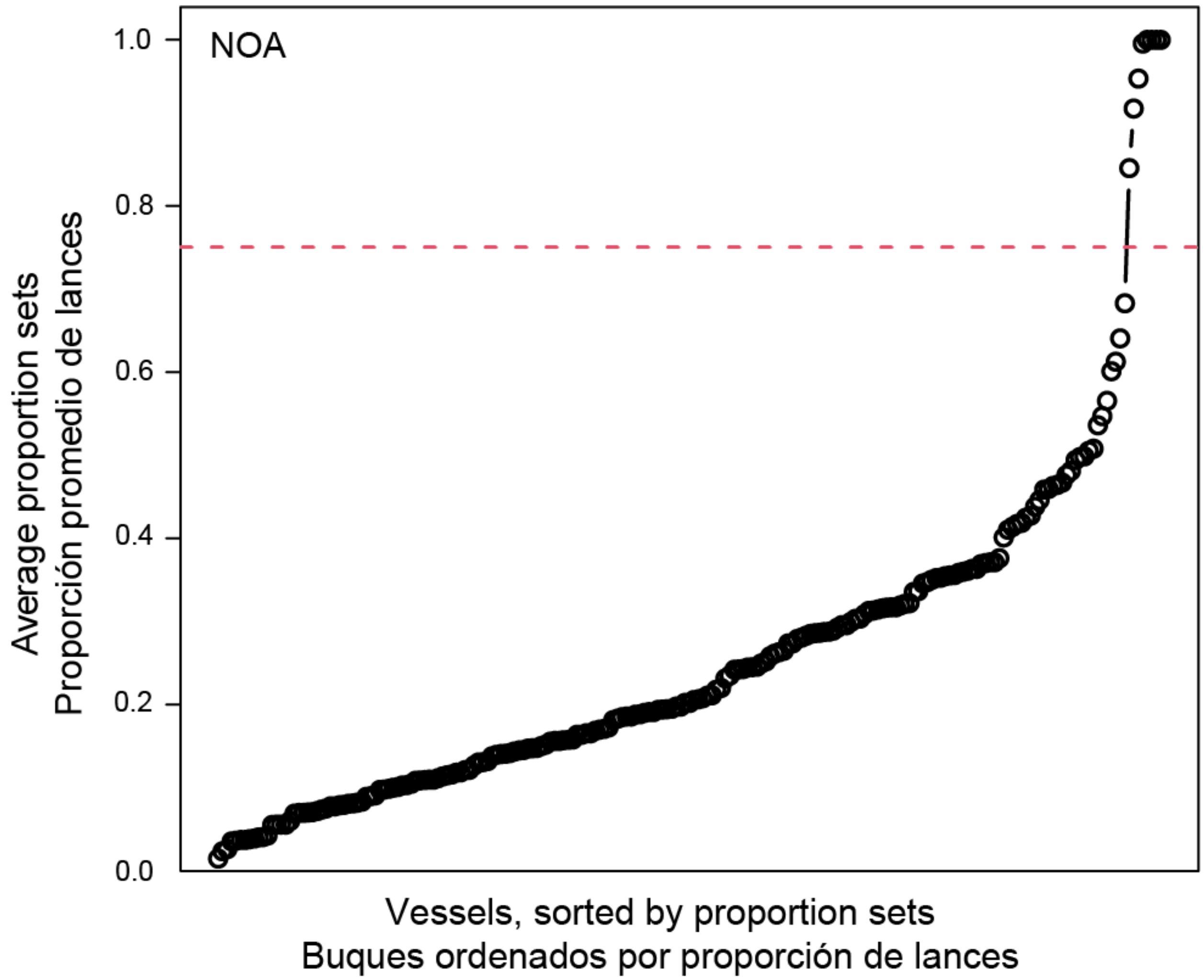

Figure 1. Plot of the average proportion of NOA sets for each vessel, ordered by the proportion.
Figura 1. Gráfica de la proporción promedio de lances NOA para cada buque, ordenados por la proporción.

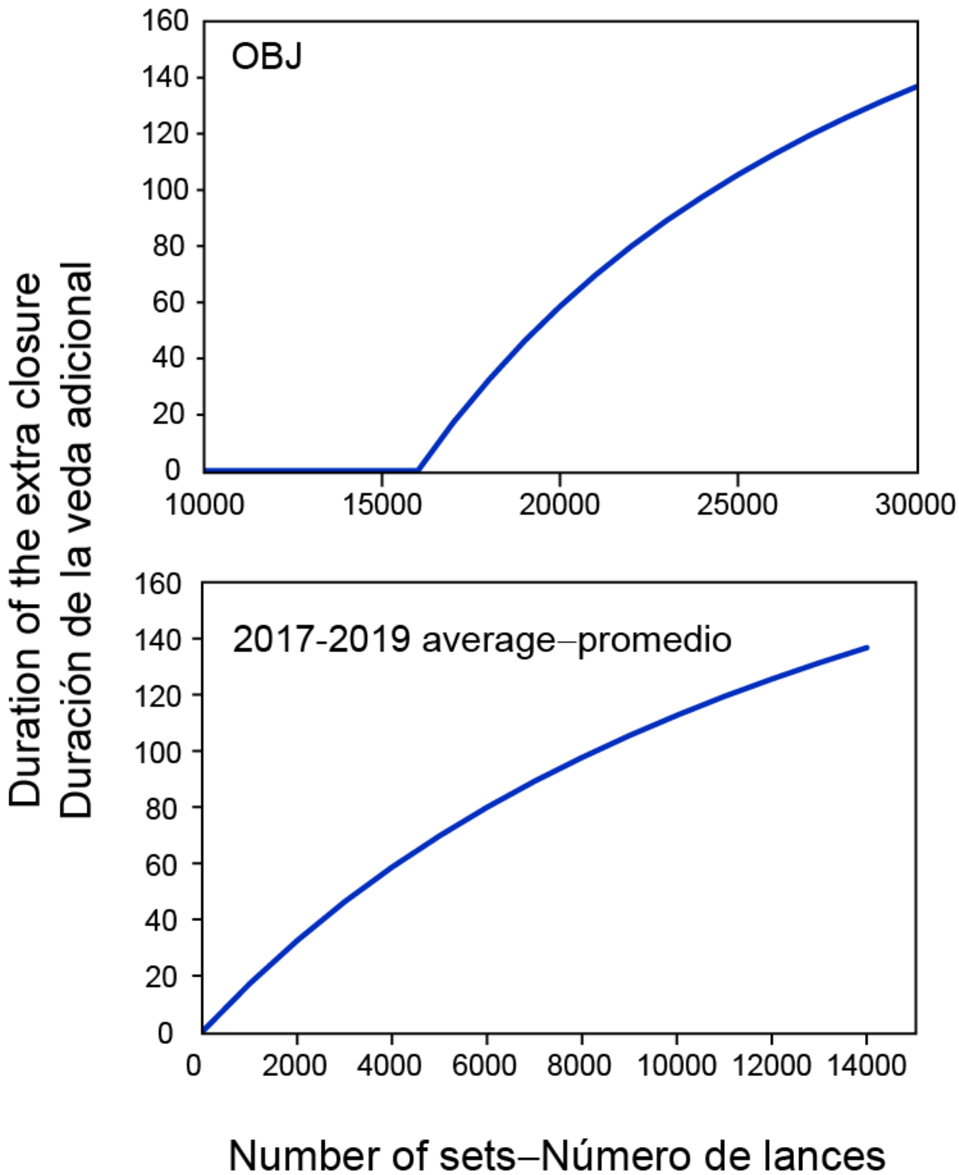

Figure 2. The duration of the extended temporal closure (in days) for a given number of OBJ sets (upper) or number of OBJ sets above the 2017-2019 average, *status quo* (lower).
Figura 2. La duración de la veda temporal extendida (en días) para un número determinado de lances OBJ (arriba) o número de lances OBJ por encima del promedio de 2017-2019, *statu quo* (abajo).

APPENDIX A. BEST SCIENTIFIC ESTIMATE (BSE) OF THE ANNUAL TOTAL NUMBER ON FLOATING-OBJECT SETS

In this section, an overview of the methodology for the best scientific estimate (BSE) of the annual total number of OBJ sets is described. Statistical details of the methodology can be found in Appendix B, and related approaches are described in Lennert-Cody and Berk (2007) and Lennert-Cody *et al.* (2013).

There are two primary data sources that can be used to obtain an estimate of the number of OBJ sets for the purse-seine fleet: 1) observer data, and 2) logbooks. Observer data are considered more reliable and contain more information than logbook data. Observer data are available for trips of all Class-6 vessels and for trips of a limited number of Class 1-5 vessels. Logbook data are often available for Class 1-5 vessels that do not carry an observer; the reporting rate has been high in recent years (SAC-08-06a) but not 100%. Logbook data will only be used when observer data are not available.

Absent any misreporting of set type, the total number of OBJ sets for a year would be the sum of the number of OBJ sets reported by observers, plus the number of OBJ sets reported in logbooks of trips without observers, adjusted for coverage if necessary (*e.g.* for any trips of Class 1-5 vessels without observers for which logbooks were not submitted to the IATTC staff). However, there is concern that misreporting of set types may occur if a management measure based on the number of OBJ sets is implemented. Therefore, before the numbers of sets by set type can be tallied, it is necessary to screen the data and correct for any misreported set types (*i.e.* those cases where the reported set type is determined to be inaccurate).

The BSE methodology can be summarized by the following steps:

1. Build a set type classification algorithm on a training data set, using information on catch composition, operational characteristics and environmental factors.
2. Using the algorithm from Step (1), predict the set type of each set in the data to be screened.
3. Evaluate the evidence for set type misreporting, and if there is strong evidence of misreporting, correct the set type of any set that was reported as either DEL or NOA but predicted to be OBJ.
4. Sum the number of OBJ sets, using the corrected set types where applicable, and adjust for coverage, if necessary, to obtain the BSE.
5. Estimate an approximate 95% confidence interval for the OBJ set BSE.

In Step (1), separate set type classification algorithms will be built for each of the two data sources because they contain different information. In particular, the logbook data have little to no information on bycatch, no information on size composition, and less information on operational characteristics, as compared to the observer data. Separate classification algorithms may be built for observer data from Class-6 vessels and from Class 1-5 vessel to avoid any potential for bias; bias could occur if any differences in fishing practices between the two vessel size class categories are not fully captured in the available information on operational characteristics.

The misclassification error rates of the algorithms that will be built in Step (1) could be influenced by several factors, including the time period selected for the training data and the information richness of the data source. For Step (1), the set type classification algorithms for analyzing data from years 2021-2023 will be built using data for years 2017-2019, to try to ensure that fishing practices in the training data are as similar as possible to the data being screened. However, data from 2010-2016 also will be used in Step (3) to evaluate the strength of evidence for misreporting (see Appendix B). To minimize the introduction of bias due to any anomalies in fishing behavior or observer coverage resulting from the COVID-19 pandemic, data from 2020 will not be used in the analysis. As regards information richness, the set type classification algorithm developed using the logbook data may have higher misclassification error rates, even in the absence of misreporting, because of the limited information available in that data source on catch composition and operational characteristics, as noted above.

To determine whether the *status quo* was maintained in a given year (*e.g*. 2021), the average number of OBJ sets for 2017 -2019 will be compared to the confidence interval for the BSE. If the average falls outside of the confidence interval of the BSE, the control rule will be evaluated.

APPENDIX B. STATISTICAL DETAILS OF THE BSE METHODOLOGY

Statistical details of each of the steps in the BSE methodology (Appendix A) are described in this appendix. In addition, examples using observer data are provided for Steps (1)-(2) of Appendix A to illustrate the random forest set type classification approach.

Set type classification algorithm

For Step (1) of the BSE methodology (Appendix A), a three-class classification algorithm for predicting set type (DEL, NOA, OBJ) will be built using the machine learning method random forests (Breiman 2001), based on the information available in the observer (logbook) data (the algorithm for logbook data will be a two-class algorithm). The random forests technique is an extension of classical classification and regression trees (CART; Breiman et al. 1984). Random forests generates predictions based on a large collection of trees (a "forest"), instead of a single tree as in CART, and has been shown to be superior to other classification methods for many problems (Breiman 2001). Each of the trees in the forest is built on a bootstrap sample of the original data. The response variable for the classification algorithm is the set type. Predictions from a random forest algorithm for new data are obtained from the proportion of trees in the forest that predicted each set type. The "majority vote" rule will be used for this purpose. That is, the predicted set type assigned to a set will be the set type that received the greatest proportion of "votes" from the trees in the forest. For example, if 60% of the trees in the forest predicted the set type should be OBJ, 30% predicted NOA, and 10% predicted DEL, the predicted set type from the forest would be OBJ. The greater the proportion of trees in the forest that predict OBJ, the stronger the evidence for the forest prediction of OBJ; *e.g.* an OBJ prediction from 95% of the trees in the forest is more convincing that one from 60% of the trees in the forest.

To illustrate the use of random forests for set type classification, the methodology was applied to observer data of Class-6 vessels for 2010-2019. The predictors used included information on operational characteristics, catch and bycatch composition, and some environmental factors (20 predictors in total were included in the algorithm). For each year, a classification algorithm was built on the data of that year. Predicted set types were assigned based on the majority vote rule. The misclassification error rate for the forest (Table B.1) is evaluated using the predictions of each of the trees in the forest on data that were not used to build the particular tree (*i.e.* these are forecast errors, based on the "out-of-bag" data). As indicated in Table B.1, the annual algorithms perform reasonably well, particularly for DEL and OBJ sets. The results in Table B.1 also show that the error rates are fairly stable over the 2010–2019 period. This suggests that, in the absence of events that might promote misreporting, large year-to-year fluctuations in algorithm performance would not be expected. It should be noted, and as explained below, these error rates do not directly carry through to the implementation of the BSE calculation, and the error rates of the actual BSE classification algorithm for observer data are likely to be lower because information on the size composition of the catch and bycatch, and additional environmental factors, will be included as predictors. Also, as noted above, it is not anticipated that the set type classification algorithm built on logbook data will perform as well because of the limited information available in that data source.

Table B.1. Misclassification error rates (proportion of sets misclassified) from random forest set type classification algorithms developed using Class-6 observer data, by year.
Tabla B.1. Tasas de error de clasificación (proporción de lances clasificados erróneamente) de los algoritmos de clasificación de bosques aleatorios de tipo de lance desarrollados a partir de datos de observadores de clase 6, por año.

Year	DEL	NOA	OBJ
2010	0.037	0.110	0.031
2011	0.020	0.091	0.039
2012	0.023	0.088	0.047
2013	0.022	0.115	0.048
2014	0.023	0.109	0.047
2015	0.022	0.109	0.056
2016	0.025	0.141	0.046
2017	0.020	0.116	0.047
2018	0.017	0.106	0.050
2019	0.011	0.065	0.040
Average	**0.022**	**0.105**	**0.045**

Classification algorithm outcomes of interest

To investigate misreporting, the outcomes from the classification algorithm that are of interest are sets for which the reported set type was DEL or NOA but the predicted set type was OBJ. The rates at which this happens for a data set are obtained from the "confusion" table. In the case of a three-class classification algorithm, the confusion table shows the number of sets for each of the 9 combinations of reported and predicted set types. To illustrate this, a set type classification algorithm (identical to those used for (Table B.1) was built on the pooled data of 2017–2019, which are the three years that will be used as the training data set for the BSE (see Appendix A). The confusion table (Table B.2) shows that, as would be expected from Table B.1, the set type of most sets is correctly predicted. The two misclassification outcomes that are of interest, with respect to future identification of misreporting, are the percent of DEL sets that were incorrectly classified as OBJ (0.21%) and the percent of NOA sets that were incorrectly classified as OBJ (3.7%). These percentages will be referred to as P_D and P_N, respectively. These values are considered the "baseline"; *i.e*. in the absence of misreporting, P_D and P_N represent the percentages of DEL and NOA sets, respectively, misclassified to OBJ. As noted above, it is likely that the algorithm performance for observer data will improve once the additional predictors are included.

For Step (2) (Appendix A), a confusion table such as that shown in Table B.2 will be created for the 2021 (or 2022 or 2023) data, using the set type classification algorithm built with 2017-2019 data. Of interest are the differences between the percentages in the 2021 confusion table, P^*_D and P^*_N, and P_D and P_N from the 2017-2019 confusion table:

$$\Delta_D = P^*_D - P_D$$

$$\Delta_N = P^*_N - P_N$$

If Δ_D and Δ_N are greater than zero, they will be taken as the estimated percentage of misclassifications that is in fact could be due to misreporting. However, before concluding that set types need to be corrected, the interannual variability in Δ_D and Δ_N, in the absence of misreporting, will be evaluated. This is because it is possible that changes in fishing strategies among years not captured by predictors used in the algorithm could lead to positive values of Δ_D and Δ_N, even when no misreporting is occurring. Note that P_D, P^*_D, and Δ_D only apply to Class-6 data.

Table B2. (a): Confusion table showing the number of sets for 2017–2019 that were correctly classified (diagonal entries) and incorrectly classified (off-diagonal entries), and the overall misclassification error for each set type. (b): The same (without the error column), but where numbers have been converted to percent. As an example of how to interpret the values in (b), the percent of DEL sets that were incorrectly classified as OBJ is 0.21% = 100 x (58 / (27756 + 370 + 58)). Rows in table (b) sum to 100% (except as a result of rounding).
Tabla B2. (a): Tabla de confusión que muestra el número de lances para el periodo 2017–2019 que fueron clasificados correctamente (entradas diagonales) y clasificados incorrectamente (entradas no diagonales) y el error de clasificación general para cada tipo de lance. (b): Lo mismo (sin la columna de error) pero donde los números se han convertido a porcentajes. Un ejemplo de cómo interpretar los valores en (b), el porcentaje de lances DEL que se clasificaron incorrectamente como OBJ es 0.21% = 100 x (58 / (27756 + 370 + 58)). Las filas en la tabla (b) suman el 100% (excepto como resultado del redondeo).

a)

		Predicted set type			**Misclassification Error**
		DEL	**NOA**	**OBJ**	
Reported set type	**DEL**	27756	370	58	0.015
	NOA	879	13356	543	0.096
	OBJ	171	1335	31536	0.045

b)

		Predicted set type		
		DEL	**NOA**	**OBJ**
Reported set type	**DEL**	98.48%	1.31%	0.21%
	NOA	5.95%	90.38%	3.7%
	OBJ	0.52%	4.04%	95.44%

Evaluating the strength of evidence for misreporting

To evaluate the strength of evidence for misreporting (Step (3) of Appendix A) in the observer (logbook) data, a simulation will be conducted with the data from 2010–2019, years when no misreporting of set types is expected. The simulation will be used to generate distributions of values of Δ_D and Δ_N that would be anticipated in the absence of misreporting. The simulation will have the following steps:

i) Select one of the 120 unique combinations of 3 years from 2010 – 2019 to be the training data, and build a classification algorithm on this data set;
ii) Using the data from each of the other 7 years, compute of Δ_{D_i} and Δ_{N_i} for each year;
iii) Repeat Steps (i)-(ii) for the remaining 119 possible 3-year training data sets;
iv) Determine the maximum values of each of the collections $\{\Delta_{D\_i}\}$ and $\{\Delta_{N\_i}\}$.

v) If either Δ_D or Δ_N for 2021 (or 2022 or 2023) exceed the corresponding maximum from Step (iv), conclude that there is strong evidence for misreporting of OBJ as DEL and/or OBJ as NOA.

Computing the BSE

If strong evidence for misreporting is identified for either data source, the BSE for the number of OBJ sets (Step (4) of Appendix A) will be computed as follows:

BSE = number of OBJ sets reported by observers +

($\Delta_{D\_observer}$ /100) x number of DEL sets reported by observers (if strong evidence of misreporting for observer DEL is found in Step (3)) +

($\Delta_{N\_observer}$ /100) x number of NOA sets reported by observers (if strong evidence of misreporting for observer NOA is found in Step (3)) +

number of OBJ sets reported in logbooks (trips without observers) +

($\Delta_{N\_logbook}$ /100) x number of NOA sets reported in logbooks (trips without observers; if strong evidence of misreporting for logbook NOA is found in Step (3))

Confidence intervals for the BSE

Assuming strong evidence for misreported set types was identified in at least one of the two data sources (observer, logbook), the BSE will include tallies of corrected set types, and thus a confidence interval for the BSE (Step (5) of Appendix A) must be computed to determine whether the *status quo* has been exceeded. A confidence interval for the BSE will be computed using the bootstrap percentile method (Efron 1982). This procedure will have the following steps:

i) Generate 1000 bootstrap data sets from the 2021 (or 2022 or 2023) observer data;
ii) For each of the bootstrap data sets, compute the observer component of the BSE (see above);
iii) Repeat Steps (i)-(ii) for the logbook data;
iv) By summing pairs of estimates from Steps (ii)-(iii), 1000 bootstrap estimates of the BSE will be generated;
v) The approximate 95% confidence interval for the BSE is the 0.025^{th} and 0.975^{th} percentiles of the distribution of the 1000 bootstrap BSE estimates.

Computer resources permitting, several thousand or more bootstrap estimates of the BSE, instead of 1000, will be generated. The random forest algorithm for the pooled 2017-2019 data took about 30 minutes to run on one computer, which suggests that generating 1000 bootstrap estimates of the BSE will require three weeks computation time on one computer.

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